

Assessment of Manufacturing Process Selection Utilizing the TOPSIS Method

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Abstract: Bancassurance. A bank and an insurance provider will enter into a "bancassurance" agreement so that the insurance provider can market to the bank's clients. The insurance provider gains from higher sales and a broader customer base without having to hire more salespeople. The marketing of insurance policies through banks is known as bancassurance. Cooperation between banks and insurance firms allows the bank to market its customers the insurance products of the associated insurance company. The Reserve Bank of India, which oversees the banking system, recognized that it was important for banks to diversify their business models and gave them permission to enter the insurance industry. In order for the insurance provider to market to the bank's customers, the bank another insurance provider will enter into a "bancassurance" agreement. More sales and a larger customer base benefit the insurance provider without the need to add more salesmen. Bancassurance refers to the sale of insurance products through banks. Banks and insurance companies can promote each other's insurance products to customers through a partnership between the two parties. Since it was crucial for banks to diversify their business models, the Reserve Bank of India, which regulates the banking system, approved their entry into the insurance sector. GRA (Gray Relational Analysis) Method, Branches, Employees, Private loans, Deposits, Customers, Life insurance premiums Alternatives Deutsche Bank, Kommerz bank, Krediet bank, Volksbanken bank. Branches, Employees, Private loans, Deposits, Customers, and Life insurance premiums. Deutsche Bank, Kommerz bank, Krediet bank, Volksbanken bank. Private loans got the first rank whereas Deposits has the lowest rank.

Keywords: Antecedents to Buying Intentions, Indian Insurance Sector, Gray Relational Analysis (GRA).

1. Introduction

In the highly competitive markets of today, product design and its manufacturing methods must be pursued simultaneously. In the course of engineering design, some of the most crucial choices are made that have the biggest impact on the overall cost. According to some estimates, "up to 70% of a product's cost" is decided during "the design phase". Concurrent engineering has gained popularity as a result of this insight. Parallelizing the tasks involved in the creation of a product is concurrent engineering [1]. To reduce "product development time, production costs, and quality flaws", concurrent engineering emphasizes the need for early manufacturing consideration in the product development process. "Design for manufacturing, or DFM", is the process of doing this while keeping a certain manufacturing method in mind. The choice of materials and manufacturing procedures is a potentially significant decision-making activity that follows DFM [2]. Different sensor signals, including "force, acceleration, temperature, pressure, and acoustic emission", are collected online to obtain process data to monitor industrial processes. Feature extraction is frequently used to minimize the dimensionality of data due to the high amount of data. When professional knowledge of manufacturing processes is accessible, efficient application-dependent features are built. Conversely, some generic data-driven dimensionality reduction strategies can be useful if there is a shortage of specialized knowledge. "Principal Component Analysis (PCA), kernel PCA, semidefinite embedding, and wavelets analysis" are a few examples of such methods [3]. Whenever a new manufacturing process is first put into use for production, it frequently happens that a complete physical understanding of the process is not available. Lithium-ion batteries, for instance, are currently joined using ultrasonic metal welding, but the technique is not well understood by experts. As a result, signal properties may be unnecessary or redundant without solid physical knowledge [4]. In such a case, feature selection is frequently used to select a small group of features for monitoring. "Feature selection" can prevent "overfitting, enhance model performance, provide more effective and economical process monitoring, and get greater insights" into the underlying techniques that produced the data by eliminating a significant amount of irrelevant and redundant characteristics [5]. "Productivity, accuracy, quality, and operation cost" are the four categories utilised to assess and determine the optimal manufacturing method. " Gravity Die Casting, Investment Casting, Pressure Die Casting, Sand Casting, and Additive Manufacturing" are five production procedures that were taken into consideration. One of the very first methods for Die Casting metal and light alloys was Gravity Die Casting. In this process, the "Molten Metal" is poured directly from a "ladle into a semi-permanent or permanent die", which is completely automated. To lessen oxidation and foaming, it is necessary to fill the die with the least amount of turbulence possible through one or more channels [6,7]. "Investment Casting" is a crucial process for generating "turbine blades with a near-net shape" because of the complexity as well as high volume

manufacturing of these parts. It is possible to control the internal geometries necessary to apply cooling techniques that permit "engine components to function at temperatures exceeding the "alloy's melting point" for better engine efficiency by employing ceramic cores during casting [8,9]. A forceful press is used to hold molten metal inside a tightly closed metal die cavity as it cools and hardens during the high-pressure Die Casting Process. The "die is unlocked, opened, and the casting is ejected" when the metal has solidified [10]. In the industrialized procedure known as "sand casting," liquid metal is poured into a hollow sand mould and allowed to solidify. The capacity of the sand-casting process to adapt is well known. Sand castings may create castings in a variety of sizes, weights, and metals with incredibly complex geometries. The "use of sand as the moulding material" is the most unique feature of the sand-casting method. [11]. The method of producing an object layer by layer is known as additive manufacturing. It is the reverse of subtractive manufacturing, which involves removing small amounts of a solid block of material at a time until the finished item is produced. Technically, the term "additive manufacturing" can apply to any procedure that involves building up a product, like moulding, but it usually refers to 3-D printing [12].

2. Materials And Methods

TOPSIS is an evaluation method that is often used to solve MCDM problems. It has several applications in practice, such as comparison of company performances, financial ratio performance within a specific industry and financial investment in advanced manufacturing systems, etc. However, there are also some limits to it [13]. The TOPSIS approach does, however, have certain downsides. The fact that TOPSIS can result in the phenomena known as the rank reversal is one of the issues it raises. "When an alternative is added to or removed from the choice issue", this phenomenon causes the order of preference for the alternatives to change [14]. "When an alternative is added to or removed from the process", it can sometimes result in what is known as a total rank reversal, when the order of preferences is completely inverted and the alternative that was previously thought to be the best now becomes the worst. In many instances, such a phenomenon might not be acceptable [15]. A variety of options must be examined and evaluated in MCDM based on several criteria. "The purpose of MCDM" is to aid the decision-maker in the "process of selecting among alternatives". In this way, practical issues are frequently defined by several opposing criteria, and it's possible that no solution can satisfy all criteria at once [16]. An answer is therefore a compromise option based on choices made by the choice-maker. Thus, TOPSIS is based on the principle that the best outcome needs to be the one that is most dissimilar from the "Negative Ideal Solution (NIS)" and most similar to the "Positive Ideal Solution (PIS)". The proximity measure is used to determine the final ranking [17,18].

Step 1: The decision matrix X, which displays how various options perform concerning certain criteria, is created.

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{1}$$

Step 2: Weights for the criteria are expressed as

$$w_j = [w_1 \dots w_n], \text{ where } \sum_{j=1}^n (w_1 \dots w_n) = 1 \tag{2}$$

Step 3: The matrix x_{ij} 's normalized values are computed as

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \tag{3}$$

Weighted normalized matrix N_{ij} is calculated by the following formula

$$N_{ij} = w_j \times n_{ij} \tag{4}$$

Step 4: We'll start by determining the ideal best and ideal worst values: Here, we must determine whether the influence is "+" or "-." If a column has a "+" impact, the ideal best value for that column is its highest value; if it has a "-" impact, the ideal worst value is its lowest value.

Step 5: Now we need to calculate the difference between each response from the ideal best,

$$S_i^+ = \sqrt{\sum_{j=1}^n (N_{ij} - A_j^+)^2} \text{ for } i \in [1, m] \text{ and } j \in [1, n] \tag{5}$$

Step 6: Now we need to calculate the difference between each response from the ideal worst,

$$S_i^- = \sqrt{\sum_{j=1}^n (N_{ij} - A_j^-)^2} \text{ for } i \in [1, m] \text{ and } j \in [1, n] \tag{6}$$

Step 7: Now we need to find the "Closeness coefficient of i_{th} alternative"

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \text{ where } 0 \leq CC_i \leq 1, i \in [1, m] \tag{7}$$

The Closeness Coefficient's value illustrates how superior the alternatives are in comparison. A larger CC_i denotes a substantially better alternative, whereas a smaller CC_i denotes a significantly worse alternative. "Productivity, Accuracy, Quality, and Operation Cost" were the four categories utilised to assess and determine the optimal manufacturing method. "Gravity Die Casting, Investment Casting, Pressure Die Casting, Sand Casting, and Additive Manufacturing" were five

production procedures that were taken into consideration. "Manufacturing productivity" is the rate at which a company creates finished goods to sell to its customers. You can evaluate an organization's total production productivity or focus on a specific line, group, or facility. Manufacturing productivity provides a gauge of a division or business's total success when paired with productivity, manufacturing cost, and revenue [19]. "Accuracy" is the level of adherence to a tolerance within a required dimension spectrum that a production machine's work exhibits. The ability of a piece of equipment to consistently generate an output over time is known as repeatability. The smallest measurement that a machine can duplicate is referred to as resolution. One of the three crucial factors in manufacturing applications is the precision of a single part as it leaves the system. The repeatability of that accuracy over numerous parts and the consistency of part dimensions over time are the other two [20]. Although there are numerous definitions of quality in manufacturing, it's crucial to keep in mind that quality is defined as achieving or exceeding customers' expectations. This implies that your items must satisfy the demands and desires of your clients, if not exceed them. Durability, dependability, and aesthetic appeal are other qualities that define quality [21]. By examining the associated overhead costs of a specific manufacturing run, the operating cost meaning is a method for determining a product's final price. "Operating costs", usually referred to as selling, general, and administrative costs, include direct costs of goods supplied and other overhead expenses. These expenses consist of rent, payroll, other overhead charges, the price of raw materials, and upkeep fees. [22].

3. Analysis And Discussion

TABLE 1. Ratings of the Manufacturing Processes

	Productivity	Accuracy	Quality	Operation cost
Sand Casting	6	2	3	5
Gravity Die Casting	8	7	9	7
Investment Casting	5	8	9	9
Pressure Die Casting	8	8	9	9
Additive Manufacturing	3	7	9	9

Table 1 shows the value of the dataset of Ratings of the Manufacturing Processes. Here evaluation parameters are "productivity, accuracy, quality, and operation cost" and alternative parameters are "Gravity Die Casting, Investment Casting, Pressure Die Casting, Sand Casting, and Additive Manufacturing".

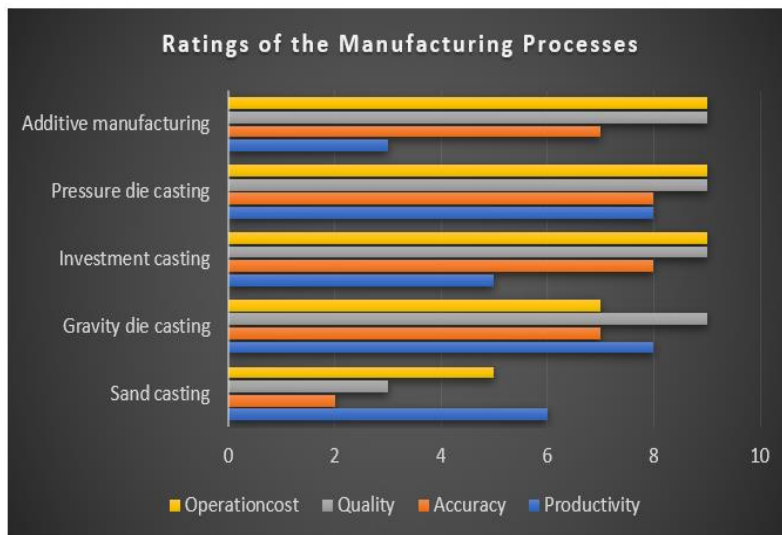


FIGURE 1. Ratings of the Manufacturing Processes

Ratings of the Manufacturing Processes are represented graphically in figure 1. Here evaluation parameters are "productivity, accuracy, quality, and operation cost" and alternative parameters are "Gravity Die Casting, Investment Casting, Pressure Die Casting, Sand Casting, and Additive Manufacturing".

TABLE 2. Normalized Data

0.4264	0.1319	0.1644	0.2808
0.5685	0.4616	0.4932	0.3932
0.3553	0.5275	0.4932	0.5055
0.5685	0.5275	0.4932	0.5055
0.2132	0.4616	0.4932	0.5055

The normalized matrix of the Ratings of the Manufacturing Processes is displayed in Table 2 above. This matrix was produced using equation three.

TABLE 3. Weight

0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

The preferred weight for the evaluation parameters is shown in Table 3. In this case, weights are equally distributed among “productivity, accuracy, quality, and operation cost”. The sum of weights distributed equals one.

TABLE 4. Weighted normalized decision matrix

0.1066	0.0330	0.0411	0.0702
0.1421	0.1154	0.1233	0.0983
0.0888	0.1319	0.1233	0.1264
0.1421	0.1319	0.1233	0.1264
0.0533	0.1154	0.1233	0.1264

Table 4 shows the weighted normalized matrix of the decision matrix and it is calculated by table 2 and table 3 using equation 4.

TABLE 5. Positive Matrix

0.1421	0.1319	0.0411	0.0702
0.1421	0.1319	0.0411	0.0702
0.1421	0.1319	0.0411	0.0702
0.1421	0.1319	0.0411	0.0702
0.1421	0.1319	0.0411	0.0702

Table 5 shows the positive matrix calculated by using table 4. The ideal best for a column is the maximum value of that column in table 4.

TABLE 6. Negative matrix

0.0533	0.0330	0.1233	0.1264
0.0533	0.0330	0.1233	0.1264
0.0533	0.0330	0.1233	0.1264
0.0533	0.0330	0.1233	0.1264
0.0533	0.0330	0.1233	0.1264

Table 6 shows the negative matrix calculated by using table 4. The Ideal best for a column is the minimum value in that column in table 4.

TABLE 7. Si Plus and Si negative

Manufacturing Process	Si Plus	Si Negative
Sand Casting	0.1051	0.1129
Gravity Die Casting	0.0884	0.1244
Investment Casting	0.1129	0.1051
Pressure Die Casting	0.0996	0.1329
Additive Manufacturing	0.1344	0.0824

Table 7 shows the Si plus and Si negative values. Difference between each response from the “ideal best (S_i^+)” is found utilizing equation 5 and the difference between each response from the “ideal worst (S_i^-)” is found utilizing equation 6.

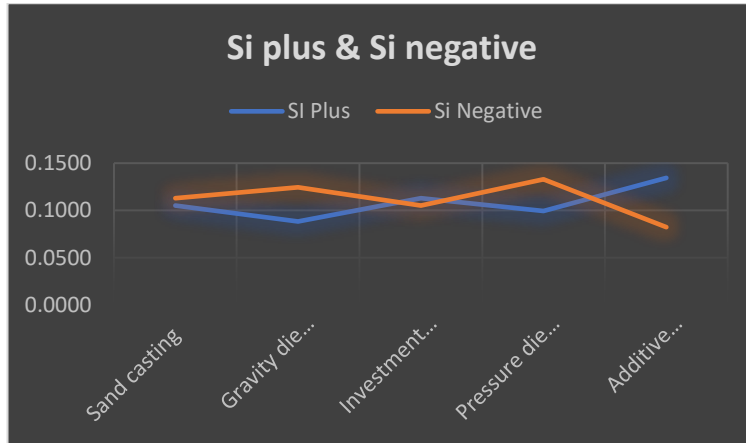


FIGURE 2. SI Plus and Si negative

Figure 2 illustrates the graphical representation of the Si plus and Si negative values. The difference between each response from the “ideal best (S_i^+)” is found utilizing equation 5 and the difference between each response from the “ideal worst (S_i^-)” is found utilizing equation 6.

TABLE 8. Closeness coefficient

Manufacturing Process	Ci
Sand Casting	0.5180
Gravity Die Casting	0.5845
Investment Casting	0.4820
Pressure Die Casting	0.5718
Additive Manufacturing	0.3801

The proximity coefficient values of the alternatives are displayed in Table 8. Equation 7 is employed in the calculation. Here Closeness coefficient value for gravity die casting is 0.5180, investment casting is 0.5845, pressure die casting is 0.4820, sand casting is 0.5718, and additive manufacturing is 0.3801.

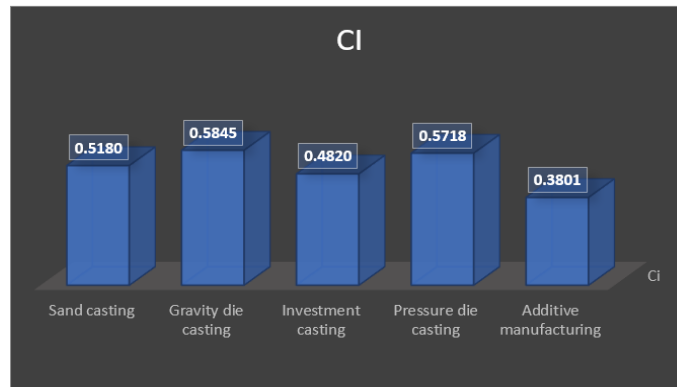


FIGURE 3. Closeness Coefficient (CCi)

Figure 3 illustrates the graphical representation of CCi. It is calculated by using equation 7. Here Closeness coefficient value for gravity die casting is 0.5180, investment casting is 0.5845, pressure die casting is 0.4820, sand casting is 0.5718, and additive manufacturing is 0.3801.

TABLE 9. Rank

Manufacturing Process	Rank
Sand Casting	3
Gravity Die Casting	1
Investment Casting	4
Pressure Die Casting	2
Additive Manufacturing	5

Table 9 shows the rank of the Manufacturing Processes. Here ranking of alternatives: gravity die casting is third, investment casting first, pressure die casting is fourth, sand casting is second, and additive manufacturing is fifth.

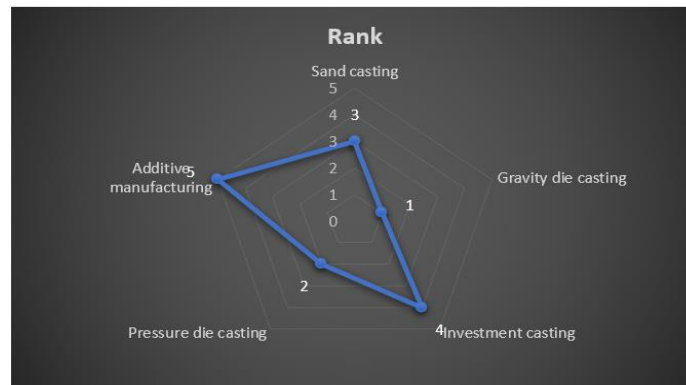


FIGURE 4. Rank

Figure 4 illustrates the ranking of U_i from Table 9. Here rank of alternatives using the TOPSIS method for gravity die casting is third, investment casting first, pressure die casting is fourth, sand casting is second, and additive manufacturing is fifth. From the result obtained from TOPSIS method optimal manufacturing process is gravity die casting followed by sand casting.

4. Conclusion

In the "design and development" of any product, choosing the production process is a difficult decision. Additionally, it is essential for successful outcomes, as well as for meeting the demands of cost-cutting and improved performance. For the selection of materials and manufacturing processes, a decision support system that combines a relational database with a multi-attribute decision-making model was described. The requirements for the manufacturing process and the material needs were determined as the choice criteria. The design specifications may be impacted by the characteristics of the structure, the product being handled, and the process in general, with the relative importance of each shifting depending on the project and demand. It is feasible to record the straightforward relationship between qualities and needs by utilising yet another matching or matched variable matching, that can be arranged into traditional relational databases. It can be challenging to choose the best multicriteria decision-making methodology from the range of options for a given application. The best manufacturing process is optimized in this paper utilizing the "technology for order of preference by similarity to ideal solution (TOPSIS)". From the result obtained from the TOPSIS method in this paper preferred manufacturing process is "gravity die casting" followed by "sand casting".

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